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Multi indicator approach via mathematical inference for price dynamics in information fusion context

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A B S T R A C T

The modelling of financial market movements and the predictions of price are deeply linked to the complexity, non linearity and the dynamism of the market itself. Many hidden factors contribute to these two subjects, which refer to the different kinds of operators (as fundamentalist and behaviourist), the different objectives amongst the retails, the institutional and business operators, the different time ranges and the different allocation plans. Moreover, the news effects on shortest time range, the induced sentiment and market movers play a key role in the modelling of the financial market. Two decision variables, named Energy E and Entropy S are introduced. Some specific values of these two variables act as attractors in the state space E-S; conesequently these two variables are useful for describing the price dynamics during the different market status (i.e. up trend, down trend, accumulation, and distribution). The result is a new decision framework, where the investor, the trader and the analyst may perform their prospects and forecasts. A multi-parametric methodology for financial trading, investment and prospects analysis is defined and introduced, by following the Prospect Theory and by assuming the price fluctuations as a dynamical process in the stochastic context.

1. Introduction

According to the results in [10,17,19,25,48] with attention to very wide markets (i.e. Currencies, Metals and Commodities), the modelling of the Financial Market is a challenging and interesting task in Information Science. The market is an open complex dynamical system, composed by a high number of heterogeneous and interactive components. The components (i.e. the agents) operate with the aim of revenue, but with different motivations, different skills, different time ranges and driven by macroeconomic and fundamental parameters, including technical ones, news, methods, general sentiment, market mover decisions, and so on. The agents interact with markets, and consequently the price movements reflect the interactions. The complexity of this scenario explains why different approaches could be profitable at some times. In fact, while in [48] one finds a system adaptation framework for identifying stock market forces, in [24,25] one can see the news and the public mood effect on price movements. In [17,29] the authors demonstrate the power of using Soft Computing for modelling financial time series and market dynamics via fuzzy analysis, while in [2,9,11] the use of computational and artificial intelligence for modelling market dynamics is shown. In [31] the author uses a credibilistic entropy of the fuzzy returns to measure the portfolio risk, which inspires to use physical variables as entropy and energy in decision making. The above

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works just represent a small sample of the variety of approaches in literature. In addition, financial markets are neither affective nor predictable and will always exist as long as Finance will exists. These and other factors motivate our effort in proposing an innovative and effective model for decision making in Finance. The use of mathematical and computational models, together with methods and techniques for analysing and understanding financial time series, is a powerful and established practice. In Financial Computing, it is a fundamental aim among others to create conceptual and practical analysis tools. These tools serve to help and support agents to better understand and recognise market dynamics. As it is well known, Bachelier was the first pioneer to consider Brownian Motion to evaluate stock options during his Financial Mathematics studies. He considered fluctuations in the price, i.e. the price at the time $t-1$ plus some random change, in terms of Random Walks, in which the price variations were entirely independent from each others. Therefore, he formulated his price model based on various independent random variables. Nowadays, many works and studies start from the important assumption that the analysis of the price dynamics concerns a non periodic and non stationary process. As in other natural phenomena, we can consider the price dynamics of a financial instrument as a digital or quantum signal, composed of price levels at different sampling rates. From this perspective, volatility change is one of the most relevant questions to assess a good investment strategy. It is deeply studied in many works, starting from the analysis on the relation between the stock volatility and real and nominal macroeconomic volatility, economic activity, financial leverage and stock trading activity [36]. As reported in [3], other studies consider the relation between volume, volatility, and market depth. Volatility is one of most relevant parameters for trading strategies, while other studies focus their attention on price dynamics. These approaches are widely used in Econophysics, as in [15,28], where a detailed description of the Generalized Hurst exponent approach is introduced for investigating the scaling structure of financial time series. Moreover, in [32] several multifractal properties of equity returns are shown. While in [4,5] the prediction of currency pair trend, using forex indicator based on fractal market hypothesis, is considered. According to the work on the Prospect Theory of Kahneman and Tversky [21], a multiparametric model for decision making in trading context is introduced. Indeed, by taking into account Information Fusion techniques and starting from a parameter set (i.e. technical indicators named CSF), we build two discrete decision variables, E and S. These are conceptually comparable with energy and entropy. When the price moves into the plane E-S, these two variables describe different prospects; so that the investors may choose the best prospect according to their trading strategies and risk profiles. Moreover, one will see how some specific prices will act as global attractors. Consequently, the price tends to the attractors, or experiences strong repulsive effects. Since trading automation is a hotspot in the field of financial research, we studied and implemented many technical indicators, which gave us trading signals. The technical indicators and the trading signals implementation involve many research groups in Financial Computing (e.g. see [1,14,18,34,46,47]). Unfortunately, each technical indicator has its pros and cons. Consequently, single indicators usually produce false signals, which may result in large money loss. One of the main advantages of multiparametric analysis (obtained through the fusion of multiple technical indicators) is the noise reduction, i.e. the reduction of false signals. Assuming that each indicator reflects certain characteristics of the market movement, we are able to select an indicator from each class: price, volatility, price oscillation and volume. The development of a new modelling technique using optimized fuzzy sets through differential evolution, for the description of emergent and international financial markets is investigated in [17]. Indeed fuzzy sets and fuzzification processes are relevant for realising multiparametric information fusion systems (sometime with inhomogeneous parameters). Information Fusion (IF) is a relatively new research field [20]. It implies that the data coming from more than one source is finally merged together in order to obtain enriched information. This technique produces a richness of details; the data precision is greater than those which could be extracted from singular information. Consequently a high level of synthesis can be obtained through a methodological and non categorical reductionism. The Information Fusion is commonly considered as a multidisciplinary research field involving different research areas (i.e. Data Mining, Knowledge Discovery, Artificial Intelligence, and so on) and specific research communities (as reported in [13,42]). Not surprisingly, many definitions and terms are derived from the above research field. For instance, the military field was the first to appreciate and use its advantages (as described in [16,33,41,44]). In literature, scientists tend to make a distinction between low and high level fusion. Most of the research studies until now have dealt with the lowest level, such as elaboration of signals and multi sensor data fusion, whereas on a higher level, the field is still quite unexplored (see for example the work in [22] on methods and algorithm for managing uncertainty). In the multi sensor fusion research field, we can find the most relevant studies, where the combined information is captured by different sensors [27]. In financial markets, the price plays the role of signal coming from a sensor for the decision process. The literature proposes three possible levels of fusion [35]:

- Feature extraction level of fusion;
- Score level of fusion;
- Decision level of fusion.

As already noticed, a model that operates at the Score Level Fusion was proposed. Additionally, we normalised and used a fuzzy process to achieve the indicator homogenization before one performs the data fusion and to build the decision variables. Our fusion strategy belongs to JDL Data Fusion Model, widely described in [26,38,39,41] as a revision of the original version. The JDL Model aims at (as described in [37]):

- Giving a point of reference for discussions about IF;
- Making it easier to understand problems for which IF techniques can be used;
- Standardising the characteristics of problems linked to the fusion process;

- Giving a framework to computerize solutions;
- Classifying different types of fusion processes.

The estimation process mainly differentiates these levels. The Level 5, added later, concerns Cognitive/User Refinement [6]. As anticipated in [2], the topic of financial markets modelling based on the interacting heterogeneity is a way of reasoning under uncertainty, due to info incompleteness. This is the typical domain where the conjugation of fuzzy reasoning and information fusion can help the agent to take decisions for forecasting uncertainty scenarios. In 2009, a fuzzy asymmetric GARCH model for the analysis of stock markets was used (as reported in [19]). The use of technical analysis and indicators for trading on financial markets is a common practice, since these tools allow for the collection of significant information about the future trends of the financial instrument of interest. According to the variety of the analysis tools available for a trader, we can distinguish three groups of relevant questions:

- Why is it correct to use a specific technical analysis tool to operate over a specific financial instrument? Could it be more correct to use another one? Who ensures that the instrument is suitable to provide information related to the type of trading that we usually take?
- How can we use the tools of technical analysis? What is the right interpretation of the information that the tool provides us? Moreover, what is the correct configuration of the parameters for the analysis tool? How can we simultaneously analyse and evaluate information from multiple indicators?
- When do we use our technical analysis tool? What market conditions are required to obtain useful information from the analysis tool and to get profitable trading?

Financial forecasting is characterised by a high degree of uncertainty and hidden relationships. Finding answers to the above questions is both important and difficult. Our model proposes a multi indicator approach, using Soft Computing and Information Fusion techniques, to provide two confidence variables which synthesise the operational suggestions. In order to ensure a more reliable indication, our approach uses a weighed linear combination of seven normalized indicators. The indicators are chosen among those most widely used by traders and investors and in relation to their use within the model. All the indicators are available on the most used trading platform. The paper is organized as follows. In Section 2 we introduce and describe the most common indicators used into our work. Section 3 provides a sketch of the strategy named MIAMI, which stands for Multi Indicator Approach via Mathematical Inference, to perform a fuzzification process for building the Critical Success Factors (CSF), i.e. those fuzzified indicators used for defining the decision variables and therefore for decision making. We introduce the Prospects Framework for Decision Making in Section 4. While in Section 5 we show tests and results. Section 6 is devoted to Conclusion and Perspectives.

2. Description of common indicators and stochastic parameters

We describe market dynamics as an interaction among many heterogeneous agents. The agents may decide in order to their market forecast, aimed to maximise or optimise the revenues. In the computational trading context for forecasting the price dynamics, the agents use some specific and well known indicators. Consequently, we consider a basic definition of agent, i.e. an agent is a computer program or a human trader as long as it follows the protocol; therefore, we consider technical trading agents, which put orders at market according to a specific technical financial indicator [29]. Then, let us introduce a brief description of some fundamental indicators used in our model. For this purpose, we define the four price levels, named High, Low, Open and Close price, which represent the maximum, minimum, initial and final price of financial instruments, within a time interval.

- The Exponential Moving Averages (EMA) Agent uses a smoothing factor for giving more importance to recent information than the previous one [12]. Formally, we have:

$$EMA_n(P, m) = P_n * \alpha + (1-\alpha) * EMA_{n-1}; \qquad \alpha = \frac{2}{m+1} \tag{1}$$

  where m is the selected period, P is the price, and n represent the nth price value.
- Parabolic SAR Agent is based on Parabolic SAR indicator, i.e. a market trend follower and market inversion indicator [43]. Formally, we have:

$$SAR_n = SAR_{n-1} + \alpha * (EPrice_{n-1} - SAR_{n-1}) \tag{2}$$

  where *EPrice* represents the Extreme Price level of the current trend. The α parameter is an acceleration factor
- The Average Directional Movement Agent, based on ADX trend indicator [43], uses the index composed by three lines, the ADX line, the $+DI$ (positive directional index) and $-DI$ (negative directional index):

$$ADX_n = \frac{EMA(|PosDI - NegDI|)}{PosDI_n + NegDI_n} * 100 \tag{3}$$

  where the EMA is calculated over the selected period, n is the nth ADX value, with

$$PosDI = \frac{EMA(PosDM)}{ATR} * 100; \quad NegDI = \frac{EMA(NegDM)}{ATR} * 100 \tag{4}$$

$$PosDM = \begin{cases} UpMove_n & \text{if} \quad UpMove_n > DownMove_n \bigwedge UpMove_n \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

$$NegDM = \begin{cases} DownMove_n & \text{if} \quad UpMove_n < DownMove_n \bigwedge DownMove_n \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$UpMove_n = Max_n - Max_{n-1}$$
$$DownMove_n = Min_n - Min_{n-1}$$

- ATR Agent uses the Average True Range indicator, i.e. a volatility indicator. ATR is a mean value of the True Range over the selected period, and it is calculated as follows [43]:

$$ATR_n = Max_n - Min_n \tag{6}$$
$$Max_n = Max_n - Close_{n-1}$$
$$Min_n = Min_n - Close_{n-1}$$

- Next Agent is based on the Stochastic Oscillator Index, i.e. a momentum indicator described in [23]. The Stochastic Oscillator is composed by two curves, as follows. The first curve is expressed by

$$\%K_n = \frac{Close_n - Lowest_P}{Highest_P - Lowest_P} * 100 \tag{7}$$

where n is the nth value of $\%K$, P is the selected period, $Highest_P$ and $Lowest_P$ are the maximum and minimum price level in the selected P period. The second curve, D_n, is a Simple Moving Average of the $\%K_n$ over the selected period.
- The Awesome Oscillator Agent considers the Awesome Oscillator, developed to estimate the market momentum [45]. Formally it can be expressed as

$$AO_n = SMA_n(P_1) - SMA_n(P_2) \quad P_1 \neq P_2 \tag{8}$$

with SMA_n Simple Moving Average on selected period P.
- The Accumulation/Distribution Agent follows the A/D Index, as in [40], based on Money Flow:

$$MoneyFlowVolume_n = \frac{(Close_n - Low_n) - (High_n - Close_n)}{High_n - Low_n} * Volume_n \tag{9}$$

and then

$$ADI_n = MoneyFlowVolume_n + MoneyFlowVolume_{n-1} \tag{10}$$

- In addition, we use the Bollinger Bands (BB) for measuring the market volatility [7]. Bollinger Bands consist of a central band, defined as a 20 period Exponential Moving Average of the price, an upper and a lower band, defined respectively by adding or subtracting two times the standard deviation to the 20 period average. Indeed, bands act as a trigger for selecting good trading opportunities. Consequently, we also have a specific agent driven by Bollinger Bands.

3. MIAMI strategy

Soft Computing is used for building the MIAMI model. Therefore, Fuzzy Logic is applied on each indicators component. In some cases, in order to transform an indicator, one considers its ON/OFF contribution to the overall linear combination of indicators. In the following, we will describe the fuzzification process. For specific agents, before to apply the fuzzification techniques, one has to consider their feedback as an ON/OFF contribution, as a switch, in order to activate or deactivate the weight that is associated to the indicators into the linear combination. Hereinafter, we will provide details of the fuzzification model. We consider indicators providing multiple information: after detecting the corresponding fuzzy set for each one, we perform an information fusion step for each component. Examples of these indicators are the Average Directional Movement Index and the Stochastic Oscillator (see Section 2). We apply an activation threshold for each indicator; for values smaller than the threshold the specific indicator contribution is not taken into account. In particular, MIAMI model analyses the indicators only if the financial instrument breaks the Bollinger Bands (the lower or the higher one); this is the case when usually a trend inversion occurs. This is the unique condition under which all indicators are calculated according to the MIAMI model; subsequently, we calculate the overall confidence index as follows:

$$F = \frac{\sum_{i=1}^{7} g_i \cdot k_i}{\sum_{i=1}^{7} g_i} \in [0, 1] \tag{11}$$

where k_i is the ith indicator, and g_i is the ith weight of the k_ith indicator. If the value of the confidence index is greater than the threshold value, we consider it as a good trend signal, and then we can give a positive signal for trading. Into the subsequent paragraphs, we give details of the weights, which are selected for the seven indicators and the used fuzzification techniques. Since the confidence index is obtained as a linear combination of Stochastic Variables, it is a stochastic variable too.

Table 1
Indicator's weight.

Indicator	g_i
EMA7 X EMA21 $\vee$ EMA7 X EMA63	1
EMA21 X EMA63	2
Parabolic SAR	3
Average directional movement index	2
Awesome oscillator	1
Stochastic oscillator	3
Accumulation / Distribution	2

Table 2
Angle value for moving averages fuzzification or angle value for +DI and -DI fuzzification.

Angle	$Variable_{fuzzy}$
$\pi/3 \leq \theta \leq \pi/2$	5
$\pi/4 \leq \theta \leq \pi/3$	4
$\pi/6 \leq \theta \leq \pi/4$	3
$\pi/18 \leq \theta \leq \pi/6$	2
$0 \leq \theta \leq \pi/18$	1
$-\pi/18 \leq \theta \leq 0$	1
$-\pi/6 \leq \theta \leq -\pi/18$	2
$-\pi/4 \leq \theta \leq -\pi/6$	3
$-\pi/3 \leq \theta \leq -\pi/4$	4
$-\pi/2 \leq \theta \leq -\pi/3$	5

3.1. Weight of indicator

A specific weight coefficient to each indicators component according to the MIAMI model is applied. These weights come from preliminary analysis, performed on the last 15 years data set. Table 1 shows the used weights, where $g_i \in [0, 3]$ means:

- 0 = not acquired;
- 1 = low;
- 2 = medium;
- 3 = high.

3.2. Fuzzification model and fuzzy sets

We are able to identify the variation range, the maximum and minimum values of indicators through statistical inference on the indicators values in a selected period. We use a fuzzy interval ranging from 1 to 5, where the maximum value is considered as the maximum degree of membership to the fuzzy set (MAX = 5), while the minimum is used as the minimum degree of membership. Then the interval between the minimum and maximum is equally allocated to the other values, so as to complete the fuzzy set. As stated before, the evaluation of indicators, their relative fuzzy contribution and the overall confidence index are computed only if the financial instrument breaks the Bollinger Bands. In this case, we find the previous opposite break, and among this time interval we calculate the confidence index. In the following we will describe the fuzzification process for each indicator.

3.3. Exponential Moving Averege (EMA) fuzzification

The activation of the Moving Averages contribution is related to the Moving Averages intersection. When a short term Moving Average significantly crosses a long term Moving Average, we identify a signal of possible trend inversion. Consequently, the weight assigned to the moving averages contribution in the confidence index computation will be significant. The model computes the angle between the two averages, for checking the occurrence of a cross between a short term and long term moving average. Then, we apply the fuzzification as in Table 2.

Consequently, we compute the average intersection contribution as

$$CSF_i \equiv AVG = \frac{|\theta_{Fuzzy}|}{5} = \frac{|variable_{Fuzzy}|}{5} \quad i \in [1, 2] \tag{12}$$

Table 3
Value for parabolic SAR fuzzification.

$PSAR_{MAX}$	$PSAR_{MAX_{Fuzzy}}$
$PSAR_{MAX} > 3/2$	5
$1 < PSAR_{MAX} \leq 3/2$	4
$2/3 < PSAR_{MAX} \leq 1$	3
$1/2 < PSAR_{MAX} \leq 2/3$	2
$0 < PSAR_{MAX} \leq 1/2$	1
$-1/2 \leq PSAR_{MAX} < 0$	1
$-2/3 \leq PSAR_{MAX} < -1/2$	2
$-1 \leq PSAR_{MAX} < -2/3$	3
$-3/2 \leq PSAR_{MAX} < -1$	4
$-3/2 < PSAR_{MAX}$	5

Table 4
ADX range fuzzification.

X_{Fuzzy}	ADX Value
1	$ADX \in [30, 41]$
2	$ADX \in [42, 53]$
3	$ADX \in [54, 65]$
4	$ADX \in [66, 77]$
5	$ADX \in [78, 90]$

where CSF_i is the acronym of *Critical Success Factor*. As anticipated, MIAMI model uses three Moving Averages (respectively with 7, 21 and 63 periods), with the following configuration and related weights:

$$\begin{cases} EMA7 \text{ cross } EMA21 \ \vee \ EMA7 \text{ cross } EMA63 & \rightarrow \ g_i = 1 \\ EMA21 \text{ cross } EMA63 & \rightarrow \ g_i = 2 \end{cases} \tag{13}$$

Then, we obtain the CSF_1 and CSF_2 from these relations.

3.4. Parabolic SAR (PSAR) fuzzification

The breaking of the Parabolic SAR level is often used to detect market inversions. Starting from the moment in which the price breaks the Parabolic SAR level, we calculate the PSAR value as follows:

$$PSAR = \begin{cases} \frac{P_{current} - PSAR_{Up}}{PSAR_{Up} - PSAR_{Down}} & \text{if we have an up break} \\ \frac{PSAR_{Down} - P_{current}}{PSAR_{Up} - PSAR_{Down}} & \text{if we have a down break} \end{cases} \tag{14}$$

Considering the maximum value as

$$PSAR_{MAX} = \max_i PSAR_i \quad i \in [1, 3] \tag{15}$$

we apply the fuzzification as shown in Table 3.

Lastly, the normalisation of fuzzy value gives the contribution of Parabolic SAR agent:

$$CSF_3 \equiv PSAR = \frac{|PSAR_{MAX_{Fuzzy}}|}{5} \tag{16}$$

3.5. Average Directional Movement Index (ADX) fuzzification

The ADX indicator provides an estimation of trend strength. We consider ADX as a two-dimensional indicator, and the fuzzification concerns the indicator value and its cross with the signal line. The ADX value has been historically analysed to establish the variation range. After this analysis, we observe that the ADX value ranges from 10 points (minimum value) to 90 points (maximum value). We can obtain a 60 points variation range by activating the first component only if its value is greater than 30 points (that indicates a possible significant trend). The fuzzification of this component (named X_{value}) is reported in Table 4, where we consider:

$$X_{value} = \frac{X_{Fuzzy}}{5} \in [0, 1] \tag{17}$$

The second component of this indicator, named Y_{value}, considers the intersection between two signal lines, $+DI$ and $-DI$. Indeed, we carried out the fuzzification according to the same criteria used for the intersection between the Moving Averages, described in Section 3.3 (see Table 2):

$$Y_{value} = \frac{|\varphi_{Fuzzy}|}{5} \in [0, 1] \tag{18}$$

Table 5
Stochastic Oscillator X_{value} fuzzification.

X_{Fuzzy}	T Value
1	$T \in [1, 6]$
2	$T \in [7, 12]$
3	$T \in [13, 18]$
4	$T \in [19, 24]$
5	$T \in [25, 30]$

Table 6
Stochastic Oscillator: overbought or oversold Y_{Value} fuzzification.

Y_{Fuzzy}	Overbought value S	Y_{Fuzzy}	Oversold value S
1	$S \in [80, 84]$	1	$S \in [16, 20]$
2	$S \in [85, 88]$	2	$S \in [12, 15]$
3	$S \in [89, 92]$	3	$S \in [8, 11]$
4	$S \in [93, 96]$	4	$S \in [4, 7]$
5	$S \in [97, 100]$	5	$S \in [0, 3]$

Then we combine these two quantities to obtain a single normalised value. The MIAMI model is able to assign different weights to the value of Y_{value} rather than X_{value}:

$$CSF_4 \equiv ADX = \left[\frac{\alpha \cdot X_{value} + \beta \cdot Y_{value}}{\alpha + \beta} \right] \in [0, 1] \tag{19}$$

where $\alpha = 1$ and $\beta = 1$; while in future, we will consider the opportunity to explore an optimised approach to achieve the best weights $\alpha \in [0, 1]$ and $\beta \in [0, 1]$.

3.6. Stochastic Oscillator (SO) fuzzification

Here we consider the Stochastic Oscillator as a multidimensional indicator. In this way, we are able to extract two types of information. For many periods, the financial instrument keeps itself in overbought/oversold area. Indeed, this tool ranges from 80 points to 100 points when the financial instrument is in an overbought condition and from 0 points to 20 points in an oversold one. By studying the X_{value} it emerges that the period in which the financial instrument remains in the overbought/oversold area is maximum 30 Periods T. This leads to the subsequent fuzzification values (see Table 5) after the introduction of the following normalization

$$X_{value} = \frac{|X_{Fuzzy}|}{5} \in [0, 1] \tag{20}$$

For the Y_{value}, we achieve the overbought condition if the value of the Stochastic Oscillator is $SO \in [80, 100]$, and we obtain the oversold condition if the value of the Stochastic Oscillator is $SO \in [0, 20]$. The fuzzification is summarized in Table 6. The normalization gives us

$$Y_{value} = \frac{|Y_{Fuzzy}|}{5} \in [0, 1] \tag{21}$$

We can combine these two contributions to obtain a single normalised value. The MIAMI model gives greater importance to Y_{value} rather than X_{value}:

$$CSF_5 \equiv SO = \left[\frac{\alpha \cdot X_{value} + \beta \cdot Y_{value}}{\alpha + \beta} \right] \in [0, 1] \tag{22}$$

where $\alpha = 1$ and $\beta = 1$; while in future, we will consider the opportunity to explore an optimised approach to achieve the best weights $\alpha \in [0, 1]$ and $\beta \in [0, 1]$.

3.7. Awesome Oscillator (AO) fuzzification

MIAMI model extracts three types of information from the Awesome Oscillator. The first type regards how many periods must elapse before a reversal occurs: MIAMI model defines this as X_{value}. The second type regards how many periods must elapse before the indicator changes its colour (i.e. green = uptrend or red = downtrend): this is Y_{value}. The third type, which is scale invariant, regards the amplitude of the indicator, that is the Z_{value}.

We observe that X_{value} indicator remains positive (or negative) generally for a maximum of 60 Periods L. Y_{value} indicator maintains its colour generally for a maximum of 30 Periods L_{Col}. Lastly, Z_{value} is the Awesome Oscillator amplitude and

Table 7
Awesome Oscillator: periods before inversion, periods before colour change and amplitude range fuzzification.

X_{Fuzzy}	$L(AO)$	Y_{Fuzzy}	$L_{Col}(AO)$	Z_{Fuzzy}	AO
1	$L(AO) \in [1, 12]$	1	$L_{Col}(AO) \in [1, 6]$	1	$AO \in [0.0, 0.001]$
2	$L(AO) \in [13, 24]$	2	$L_{Col}(AO) \in [7, 12]$	2	$AO \in]0.001, 0.002]$
3	$L(AO) \in [25, 36]$	3	$L_{Col}(AO) \in [13, 18]$	3	$AO \in]0.002, 0.003]$
4	$L(AO) \in [37, 48]$	4	$L_{Col}(AO) \in [19, 24]$	4	$AO \in]0.003, 0.004]$
5	$L(AO) \in [49, 60]$	5	$L_{Col}(AO) \in [25, 30]$	5	$AO \in]0.001, 0.005]$

Table 8
Accumulation/Distribution delta variation range fuzzification.

A/D_{Fuzzy}	δ_n
1	$\delta_n \leq \delta_{Max_{norm}}$
2	$\delta_{Max_{norm}} < \delta_n \leq 2 \cdot \delta_{Max_{norm}}$
3	$2 \cdot \delta_{Max_{norm}} < \delta_n \leq 3 \cdot \delta_{Max_{norm}}$
4	$3 \cdot \delta_{Max_{norm}} < \delta_n \leq 4 \cdot \delta_{Max_{norm}}$
5	$\delta_n \geq 4 \cdot \delta_{Max_{norm}}$

ranges in the interval $AO \in [0.0; 0.005]$. Therfore, we have the subsequent fuzzification (see Table 7) and normalisation:

$$X_{value} = \frac{X_{Fuzzy}}{5} \in [0, 1]; \quad Y_{value} = \frac{Y_{Fuzzy}}{5} \in [0, 1]; \quad Z_{value} = \frac{Z_{Fuzzy}}{5} \in [0, 1]. \tag{23}$$

Finally, we build a single normalised value through the components combination, i.e.

$$CSF_6 \equiv AO = \left[\frac{\alpha \cdot X_{value} + \beta \cdot Y_{value} + \gamma \cdot Z_{value}}{\alpha + \beta + \gamma} \right] \in [0, 1] \tag{24}$$

where $\alpha = \beta = 1 = \gamma = 1$; while in future, we will consider the opportunity to explore an optimized approach to achieve once again the best weights $\alpha \in [0, 1]$, $\beta \in [0, 1]$, $and \gamma \in [0, 1]$.

3.8. Accumlation/D istribution (A/D) fuzzification

MIAMI model uses Accumulation/Distribution indicator as a price weighed diagram compared to the volumes. We calculate the normalised maximum variation over the last $k = 5$ values of the Accumulation/Distribution:

$$\delta_{Max} = \max_i |A/D_{i+1} - A/D_i| \quad i \in [1, k-1] \tag{25}$$

and the normalisation of δ_{Max} defined as

$$\delta_{Max_{norm}} = \frac{\delta}{k} \tag{26}$$

Consequently, we obtain the fuzzy value of δ, related to the maximum variation in the selected period, as follows (see Table 8).

Hence, we obtain the normalised value of A/D:

$$A/D = \frac{A/D_{Fuzzy}}{5} \quad \in [0, 1] \tag{27}$$

3.9. Decision variable

Finally, we can compute the output overall confidence index, as:

$$F = \frac{\sum_{i=1}^{7} g_i \cdot k_i}{\sum_{i=1}^{7} g_i} \in [0, 1] \tag{28}$$

where k_i is the ith indicator, and g_i is the ith weight of the k_ith indicator. Then, we can build a prospect framework to assist the analyst or trader in decision making. This framework is realised using two decision variables, called Energy and Entropy. The Energy variable E is the confidence index F, and it represents the level or the strength of forecasting. Following the terminology used in some fundamental works, as in [8,30], we introduce a disorder measure of price dynamics which is named Entropy S. The Entropy S represents the displacement of the current value of E, with respect to an E_{Max}, evaluated on every specific timeframe. Hence, Entropy S represents the energy E that is lost in the dynamical pricing evolution. It is a dissipative process due to the price fluctuations. Formally, we have

$$E_{Current} = F = \frac{\sum_{i=1}^{7} g_i \cdot k_i}{\sum_{i=1}^{7} g_i} \in [0, 1]; \quad S_{Current} = E_{Max} - E_{Current} \tag{29}$$

By normalising E_{Max} we obtain

$$S_{Current} = 1 - E_{Current} \in [0, 1] \tag{30}$$

The objective is to estimate the prospect of investments in terms of probability, by customising the stochastic variables CSF_i, E and S in the range [0,1]. Prospects with high E and low S will correspond to scenarios with well-defined trends; otherwise, if E is low and S is high, it means that the energy of phenomena (i.e. the energy of price dynamics) is spent or dissipated for lateral movements (i.e. sideways trend).

4. Prospect framework for decision making

While in the previous sections we considered the normalised stochastic parameters (i.e. the *CSFs* and the decision variables E and S), in this section, we consider the variables without normalisation, to build the prospect infrastructure. In this way the couple *(e,s)* (i.e. E and S in a non normalised version) helps us to estimate better the state of the market as points in the *e-s* scenario. The prospects will be given by a four dimensional vector *(e,E,s,S)*. Consequently, the couple *(e,s)* determines the state of the financial instrument in the space state, while the couple *(E,S)* refers to the probability of directional or lateral market. We define Prospects Space by the four dimensional space containing the vectors *(e,E,s,S)*. Initially, Mathematicians developed the Chaos and Complexity Theory with the name of *"Ergodic Theory"*. The Ergodic Theory regards mainly the mathematical study on average and long term behavior of dynamic systems. As known from the Greek, *érgon* means energy and *odòs* stays for road or path. Therefore, Boltzmann introduced this term referring to the property that different microscopic states could correspond to a single macroscopic state. In fact, if we consider the seven dimensional vector $CSF = (CSF_1, \ldots, CSF_7)$, in two different states, the two microscopic state could correspond to the same macroscopic state *(E,S)*. We define the following stochastic variables, starting from their normalised versions as seen above, i.e. we define the microstate as the market state described by the seven dimensional vector $csf = (csf_1, \ldots, csf_7)$ if $csf_i = 5 \cdot CSF_i$ then $csf_i \in [0, 5]$ where:

1. 0 = not acquired;
2. 1 = low;
3. 2 = medium low;
4. 3 = medium;
5. 4 = medium high;
6. 5 = high.

On the other hand, we define macrostate as the state of the market described by the two dimensional vector of decision variables $ms = (e, s)$, with

$$e = \sum_{i=1}^{7} \alpha_i \cdot csf_i \quad \text{and} \quad s = \frac{1}{7} \sum_{i=1}^{7} \alpha_i \cdot |csf_i - m_i| \tag{31}$$

where m_i is the median value of csf_i and α_i are normalization factors, whose values are here fixed to 1 in absence of market historical data set, but in general they are ranging into the real interval [0,1]. As we will see below, $e \in [7, 35] \subset \mathbb{N}$ (if all csf_i are acquired, i.e. are not null), while $s \in [0, 12] \subset \mathbb{N}_0$. Mathematically, the number of possible prospects is very high. In fact, this number is expressed in terms of an ordered selection with repetition of 7 elements from the set *{1,2,3,4,5}*, and therefore, it is given by 5^7 different possibilities, that is equal to 78,125 possible prospects. For analysis purposes, it is useful to cluster the 78,125 scenarios in classes with common properties. Here we present a statistic clustering in order to perform an analysis of the deviations from ground states; hereinafter, we construct a more suitable classifications in terms of evolutionist dynamics.

The prospects, clustered in classes, play a very important role; in fact, this technique allows the modeling of unstructured information, in the analysis phase; then this enables the building of analytical and automatic decision support models. Furthermore, the use of stochastic critical success factors shows how we can view the 78,125 prospects as microscopic states. The huge number of microscopic states can be associated with a reduced number of macroscopic states, expressed in terms of decision variables e and s, whose number is drastically lower than the number of microstates. However, this denotes a macroscopic states degeneration. The Prospects Environment *PE* (i.e. the space where prospects live) can be deconstructed in 13 subsets (or sub prospects environment). They are obtained by taking into account the characterization. The term characterization refers to the different manners in which we can obtain the *n-tuple* of the seven indexes csf_i. Specifically, we distinguish the following 13 characterizations, by assuming that all seven csf_i are acquired (i.e. the most general case):

Table 9
Prospect environment and properties.

PE	Characterization	#of subPE	#of States i.e. prospects	e	s
PE_1	7	5	$5 \cdot (7!/7!) = 5$	[7, 35]	0
PE_2	$6+1$	20	$20 \cdot (7!/6!) = 140$	[8, 34]	[1, 4]
PE_3	$5+2$	20	$20 \cdot (7!/5! \cdot 2!) = 420$	[9, 33]	[2, 8]
PE_4	$5+1+1$	30	$30 \cdot (7!/5!) = 1260$	[10, 32]	[2, 7]
PE_5	$4+3$	20	$20 \cdot (7!/4! \cdot 3!) = 700$	[10, 32]	[3, 12]
PE_6	$4+2+1$	60	$60 \cdot (7!/4! \cdot 2!) = 6300$	[11, 31]	[3, 11]
PE_7	$4+1+1+1$	20	$20 \cdot (7!/4!) = 4200$	[13, 29]	[4, 9]
PE_8	$3+3+1$	30	$30 \cdot (7!/3! \cdot 3!) = 4200$	[12, 30]	[4, 12]
PE_9	$3+3+2$	30	$30 \cdot (7!/3! \cdot 2! \cdot 2!) = 6300$	[14, 29]	[4, 11]
PE_{10}	$3+2+1+1$	60	$60 \cdot (7!/3! \cdot 2!) = 25200$	[14, 28]	[5, 11]
PE_{11}	$3+1+1+1+1$	5	$5 \cdot (7!/3!) = 4200$	[17, 25]	[6, 9]
PE_{12}	$2+2+2+1$	20	$20 \cdot (7!/2! \cdot 2! \cdot 2!) = 12600$	[16, 26]	[6, 10]
PE_{13}	$2+2+1+1+1$	10	$10 \cdot (7!/2! \cdot 2!) = 12600$	[18, 24]	[7, 10]

Fig. 1. Partion of states space. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1. 7: Seven equal indices;
2. 6 + 1: Six equal indexes and a different one;
3. 5 + 2: Five equal indexes and two different ones (with the same value);
4. 5 + 1 + 1: Five equal indexes and two different ones;
5. 4 + 3: four indexes with a value and three with another one;
6. 4 + 2 + 1: four indexes with a value, two with another one and the last index with a third different value;
7. 4 + 1 + 1 + 1: four indexes are equal and three are different;
8. 3 + 3 + 1: three indexes with a value, three with another one and the left one with a third value different from the previous ones;
9. 3 + 2 + 2: three indexes with a value, two with another one and two with a third value different from the previous ones;
10. 3 + 2 + 1 + 1: three indexes with a value, two with another one, and the remaining two with two different values;
11. 3 + 1 + 1 + 1 + 1: three indexes equal and four ones with a different value;
12. 2 + 2 + 2 + 1: two indexes with a value, two with another value, two another one different from the previous and a single one;
13. 2 + 2 + 1 + 1 + 1: two indexes with a value, two with another one, and three indexes with three different value respectively.

In Table 9. we summarise the previous results giving further details.

The total number of *sub PE* is equal to 330 as given by the ordered selection with repetition of $n = 5$ elements taken at $k = 7$ per time, i.e. $C_{5,7} = \binom{5+7-1}{7} = \frac{11!}{7! \cdot 4!} = 330$. To understand the power of the given representation, this number of *sub PE* has to be compared with the numbers of microstates, i.e. prospect, that is 5^7. Fig. 1 shows a partition of *PE* in nine areas, as described in the following:

- I low entropy, low energy (blue);
- II low entropy, average energy (light blue);
- III low entropy, high energy (green);
- IV average entropy, low energy (lilac);
- V average entropy, average energy (white color);
- VI average entropy, high energy (pink);
- VII high entropy, low energy (yellow);
- VIII high entropy, average energy (orange);
- IX high entropy, high energy (red).

It is evident that the best states belong within the green area, i.e. to the region III, that is the case of high energy and low entropy. This means that the market has a fast dynamic that does not create disorder or dissipation (strong trends). The two worst states set (for various reasons, which will be described below) belong to the area VII (yellow) and IX (red). The area VII (Yellow) describes states, or prospects, characterised by low energy and high entropy, the worst states if the objective is to bring the market to greater balanced state (it will take a long time to rebalance those markets whose states

ENERGY \ ENTROPY	0	1	2	3	4	5	6	7	8	9	10	11	12
7	1												
8		7											
9			28										
10				84									
11				35	175								
12			21		140	294							
13		7		105		350	413						
14	1		42		315		700	462					
15		7		147		735	35	1050	441				
16			28		392	105	1260	140	1260	350			
17				84	126	735	420	1680	350	1190	210		
18				77	168	525	1050	1050	1680	560	840	105	
19			28		350	252	1365	1085	1680	1295	630	420	35
20		7		147		980	266	2310	945	1890	770	420	140
21	1		42		462		1820	420	2730	840	1260	420	140
22		7		147		980	266	2310	945	1890	770	420	140
23			28		350	252	1365	1085	1680	1295	630	420	35
24				77	168	525	1050	1050	1680	560	840	105	
25				84	126	735	420	1680	350	1190	210		
26			28		392	105	1260	140	1260	350			
27		7		147		735	35	1050	441				
28	1		42		315		700	462					
29		7		105		350	413						
30			21		140	294							
31				35	175								
32				84									
33			28										
34		7											
35	1												

Fig. 2. The picture shows the distribution of states into the plane energy *e* and entropy *s*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

lie in the yellow area). The area IX (red) describes high energy and high entropy states. Therefore, it represents markets characterised by a high speed, close to the chaos. This means that financial operators will have short time to take decisions, but if the decisions are right, the market will spend short time to turn into more stable area. The last extreme area is the area I (blue), characterised by low energy and low entropy. With low energy, the market will be very slow with small disorder. This area typically describes night trading situation with small trend. In addition to these areas, which we can consider more extreme than others, we have to take into account the areas represented by most hybrid prospects. These areas are the area II (light blue), the area IV (lilac), the area VI (pink) and the area VIII (orange). The II and VI areas present the best prospects in terms of market in trends. The entropy is always lower than the average energy in these areas. For the trading strategies based on lateral movements (i.e. sideways market), where the market entropy is more effective rather than the market energy, the areas IV and VIII are more suitable than the other ones. Among hybrid scenarios the area VIII is the worst one in terms of trends trading, while it is the best for trading strategies thought for lateral movements across the market. Finally, the area V (white) is characterised by a complete balance between entropy and energy. This means a continuous alternation between trend and lateral phases. The areas VII and IX are forbidden for trading, since the area VII represents the chaos at low energy, while the area IX denotes the presence of chaos at high energy. Fig. 2 gives a sketch of the plane e-s. We report in grey the range of 13 levels of admissible entropy and 29 levels of admissible energy with ranges on [0,12] and [7,35] respectively. Fig. 2 reports the number of microstates (i.e. prospects) corresponding to a fixed couple *(e,s)*, i.e. corresponding to a fixed macrostate (i.e. *sub PE*).

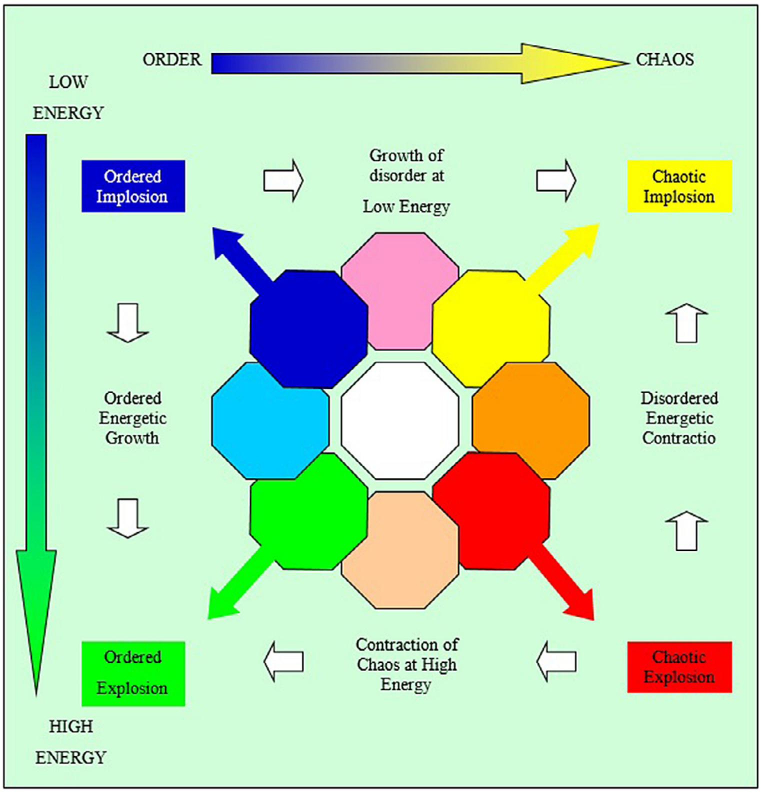


Fig. 3. Sketch of prospects and transitions among them.

At this point we summarize the essential aspects of the transitions from one prospect to another, in terms of energy and entropy useful for forecasting and building trading strategies. In particular, proceeding from left to right, the entropy increases and so we move from more ordered states of market, to more disordered ones. Proceeding from top to bottom, the states transit from low energy states to others with higher energy. As anticipated, the overall picture is as follows:

i Blue: ordered states with low dynamics;
ii Light blue: ordered states with an average dynamics;
iii Green: ordered states with high dynamics;
iv Lille: averagely ordered states with low dynamics;
v White: averagely ordered states with average dynamics;
vi Pink: averagely ordered states with high dynamics;
vii Yellow: disordered states with low dynamics (i.e. ”cold chaos” or low energy chaos);
viii Orange: disordered states with an average dynamics;
ix Red: disordered states with a high dynamics (i.e. “hot chaos” or chaos at high energy).

Therefore the blue area reflects a freezing in terms of energy and entropy, which corresponds to a market close to the doldrums. Making a comparison with seasons it is equivalent to winter. In these cases, it would be difficult, laborious and time consuming making the market revert to an area of higher dynamics. The Green area is characterized by high ordered and energetic states. It represents a market in optimal conditions. Using the metaphor of seasons, it is equivalent to Spring. The Red area is related to high energetic and high disordered states. Using the metaphor of seasons, it is equivalent to a very hot Summer season. The institutions and the private investors will have to put big attention to the strategies since market is on the border of catastrophic situation, such as speculative bubbles, natural disasters, wars or conflicts, significant economic imbalances, failures of state policy or monetary policy. In other words this situation carries the market out of statistical control. The Yellow area is characterized by states with a low energy and a high disorder. The rebalancing of a market states in this area is a very heavy task and requires time and resources, since the energy is low. Indeed one is dealing with chaotic off scale states in these cases. Continuating with the metaphor of seasons, the yellow area can be associated to the Fall. The other areas are equivalent to a change of seasons. Consequently, these areas exhibit mixed properties. An exception is the white area, which reflects a neutral situation of market. Fig. 3 sketches states and transitions of market in schematics way.

Thanks to the previous description, we represent the market in terms of states and dynamical changes, or transitions between states or prospects. This would allow forecasts on market movements, which are comfortable, stable and accurate.

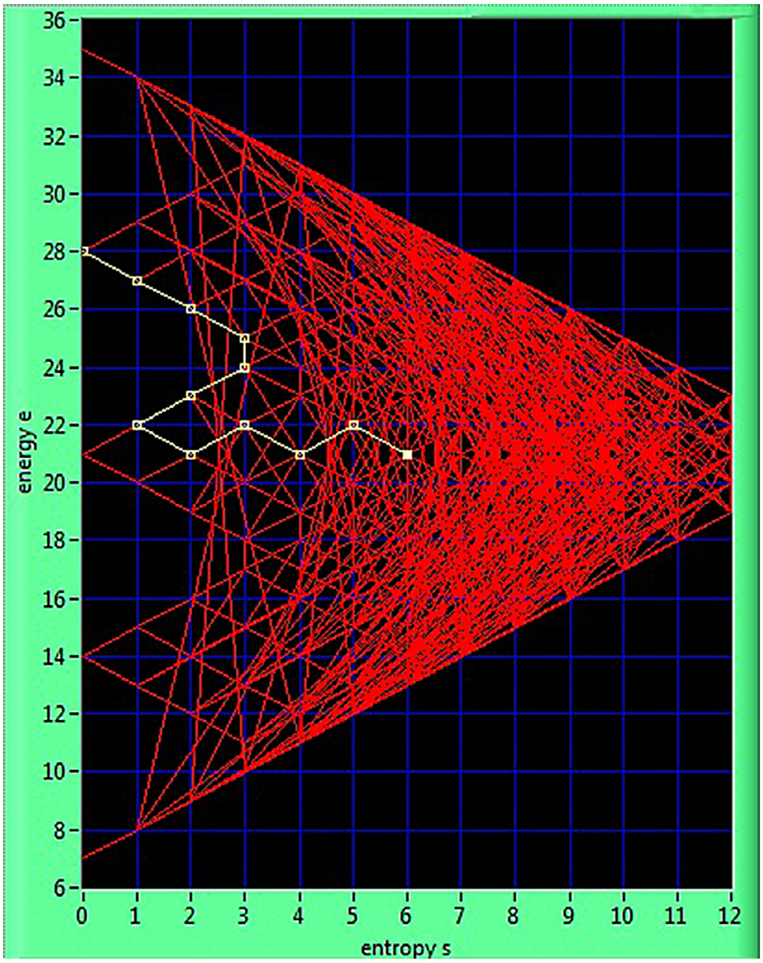


Fig. 4. A typical market transition trough different prospects or states.

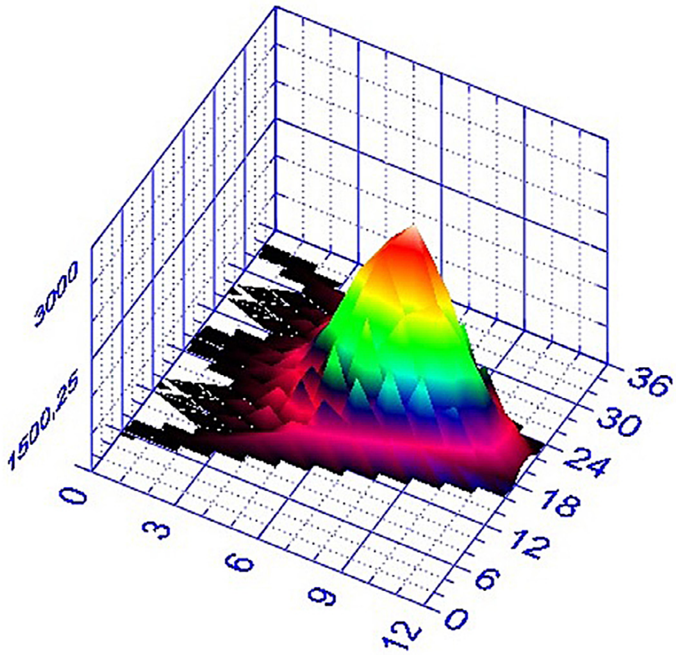
Fig. 4 shows a typical transition among states into MIAMI platform. Indeed from this picture, the market moves towards an attractor at a higher level of energy than the starting one, and a movement towards a very ordered state. To be specific, we define fundamental attractors those states with $s = 0$ at different energies.

At the end, we show the prospects distribution for each area, and the same results in terms of probability (in brackets) in Fig. 5. Moreover we plot the 3D distribution related to the number of states with respect to *e* and *s* variables.

In conclusion, we put in evidence that the full prospect analysis will be realised thanks to the four dimensional vector *(e,E,s,S)*, as anticipated at the beginning of this section, where *E* and *S* represent the probabilities to obtain a state with the energy *e* and the entropy *s* respectively. This section is fully inspired by G.Iovane in terms of his previous work in Mathematical Modelling for Security.

5. Tests environment

A test environment for validating MIAMI model and to estimate its reliability was developed. We analysed different financial instruments, at different timeframes and under varying assumptions, in order to obtain stable results. The tests were carried out using the MetaTrader 4 strategy tester. In order to ensure the maximum reliability of the tests, we also integrated complete historical data. With this aim, we collected the historical data for five forex majors, namely EURJPY, EURUSD, GBPJPY, GBPUSD and USDJPY from various open sources. Subsequently, we merged these data, coming from heterogeneous sources, to achieve the maximum completeness in the data. This helps to avoid the presence of “wholes”, as it often happens when handling with historical data. We also changed the temporal period of testing, starting from one month, then testing over six months up to finishing with an eighteen months testing period. In all cases the quality of the MetaTrader testing model was not smaller than 90%, which guarantees the consistency of the historical data, used by the authors and the repeatability of the tests. In the following, we show the results obtained from the execution of the strategy based on MIAMI model on the five financial instruments for two different time periods, six and eighteen months. The para-



485 (0,62%)	5110 (6,54%)	0 (0%)
785 (1%)	45780 (58,60%)	20370 (26,07%)
485 (0,62%)	5110 (6,54%)	0 (0%)

Fig. 5. In the lower part of the picture we show the Absolute frequency of prospects into the specific nine area with relative probability (percentage) for each Area, while a typical states distribution with respect to energy *e* and entropy *s* is represented into the upper part of the picture.

Table 10
Performance results over six months, from 2015.01.01 to 2015.06.30.

Cross	#Ops	#Profit Ops	#Loss Ops	%Profit Ops	%Loss Ops	%Max DD
EURJPY	299	189	110	63.21%	36.79%	2.18%
EURUSD	301	204	97	67.77%	32.23%	0.70%
GBPJPY	424	272	152	64.15%	35.85%	2.74%
GBPUSD	319	210	109	65.83%	34.17%	1.15%
USDJPY	248	158	90	63.71%	36.29%	1.34%

metric configuration has been chosen starting to test the strategy on a short time period, i.e. one month; we selected the first working configuration of parameters and extended the time interval to prove the consistency of the performances. We performed the initial tests with variable spread value (initialized with its actual value at the moment of the tests), and with spread value fixed to its more frequent values within its variation range. This helps to maintain the independency from the value of the spread, which represents the operational costs and can vary significantly according to the volatility. The results have shown that the entity of the spread does not affect the efficiency of the strategy also in these cases. Consequently, the approach is not dependent on the volatility of the market. Therefore it is well suited for both low and high volatility situations. The results could be further improved simply by choosing the best parametric configuration corresponding to each different time period. In Tables 10 and 11 we show the results, in terms of profit and loss trades, obtained on two different time intervals. We denote with “Cross” the financial instrument, “#Profit Ops” the number of operations in profit, “#Loss Ops” the number of operations in loss, “%Profit Ops” the percentage of operations in profit, “%Loss Ops” the percentage of operations in loss, and with “%Max DD” the percentage of Maximum DrawDown.

The similarity of the values proves that a particular performance is not due to a specific testing period, which could have been influenced by extraordinary macroeconomic events, neither does it depend on a given financial instrument. The tests were all performed with spread value equal to its current real value, which is of course a strong constraint as it means that the operational costs were maximum corresponding to high volatility market situations. Fig. 6 exhibits the best and

Table 11
Performance results over eighteen months, from 2014.01.01 to 2015.06.30.

Cross	#Ops	#Profit Ops	#Loss Ops	%Profit Ops	%Loss Ops	%Max DD
EURJPY	789	513	276	65.02%	34.98%	4.83%
EURUSD	731	491	240	67.17%	32.83%	2.40%
GBPJPY	1092	736	356	67.40%	32.60%	6.16%
GBPUSD	734	481	253	65.53%	34.47%	3.18%
USDJPY	621	391	230	62.96%	37.04%	4.83%

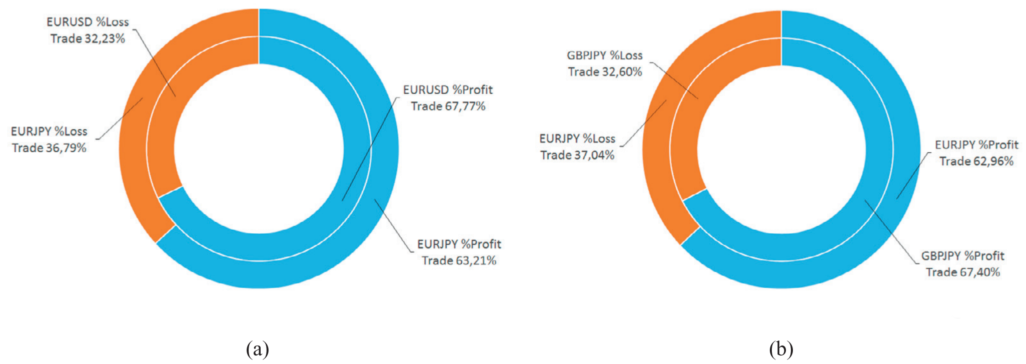


Fig. 6. The best and worst result on six and eighteen months test period, from 2015.01.01 to 2015.06.30 (a) and from 2014.01.01 to 2015.06.30 (b).

the worst performance for each of the time intervals of testing, respectively six months (a) and eighteen months (b). The stability of the results is evident as the worst and the best values are very close to the average performance result.

Finally, it must be highlighted that the tests have been performed on the different financial instruments with the same parameters values; this implies that the results will certainly improve by selecting the best configuration for each financial instrument. In conclusion, we have tested the model with an automatic trading strategy executed on different financial instruments, at different time frames, for different time intervals and with variable spread values. The results highlight MIAMI model does not depend on: (i) the financial instrument, (ii) the market volatility, (iii) the spread value, (iv) the timeframe and (v) the trading time interval.

6. Conclusions and future perspectives

According to the Prospect Theory of Kahneman and Tversky [21] and considering the price fluctuations as a dynamical process, we realised a Multiparametric Analysis Framework for Decision Making in Financial Investments on short timeframes (MIAMI model). This result was obtained by applying specific techniques, belonging to Knowledge Discovery, Technical Analysis, Information Fusion and Soft Computing. After a specific fuzzification process, the various contributions were fused into two decision variables, named Energy and Entropy. These are useful for describing trend and oscillation periods, in a prospect plane E-S, where price dynamics evolves during price movements. While the fuzzy indicators (named Critical Success Factors) could generate false signals if considered individually, the decision variables, *E,S* define more stable prospects. Moreover, we achieve more reliable and better quantified forecasts, from a probabilistic point of view, by analysing the price dynamics into the plane E-S. Lastly, while in the time-price space the price suffers from high fluctuations, it appears more stable in the E-S plane. Consequently E-S space gives the opportunity to understand and forecast price behaviour driven by market movers better and better. The tests have been performed on different short timeframes, but MIAMI model can be used on all timeframes, provided that a parametric optimisation has been performed. The next step will concern further tests on other financial instruments. In addition, we could also perform a parametric optimisation for each considered financial instrument, in order to achieve indipendent optimal parameter configurations. Furthermore we will analyse entries and exits of the trading strategy, in order to define constraints, which are able to improve the timing of the agents. At this moment, MIAMI model provides the trader with a clear and reliable suggestion machine concerning the prospects scenario and the trading strategies, driven by an Information Fusion technological solution.

References

[1] M. Adya, F. Collopy, How effective are neural networks at forecasting and prediction? a review and evaluation, J. Forecasting 17 (1998) 481–495.
[2] G. Armano, M. Marchesi, A. Murru, A hybrid genetic neural architecture for stock indexes forecasting, Inf. Sci. 170 (2005) 3–33.
[3] H. Bessembinder, P. Seguin, Price volatility, trading volume and market depth: evidence from futures market, J. Financ. Quant. Anal. 28 (1) (1993) 21–39.
[4] J.M. Blackledge, Application of the fractional diffusion equation for predicting market behaviour, IAENG Int. J. Appl. Math. 4 (3) (2010) 130–158.

[5] J.M. Blackledge, K. Murphy, Predicting currency pair trends using the fractal market hypothesis, in: Irish Signal and Systems Conference, Trinity College Dublin, 2011.
[6] E. Blasch, S. Plano, JDL level 5 fusion model: user refinement issues and applications in group tracking, SPIE Aerosense 4729 (2002) 270–279.
[7] J. Bollinger, Bollinger on Bollinger Bands, McGraw Hill, 2002.
[8] G. Caginalp, G. Ermentrout, A kinetic thermodynamics approach to the psychology of fluctuations in financial markets, Appl. Math. Lett. 3 (1990) 17–19.
[9] R. Cavalcante, R. Brasileiro, V. Souza, J. Nobrega, A. Oliveira, Computational intelligence and financial markets: a survey and future directions, Expert Syst. Appl. 180 (2016) 194–211.
[10] T. Chen, F. Chen, An intelligent pattern recognition model for supporting investment decisions in stock market, Inf. Sci. 346–347 (2016) 261–274.
[11] C. Cheng, T. Chen, L. Wei, A hybrid model based on rough sets theory and genetic algorithms for stock price forecasting, Inf. Sci. 180 (2010) 1610–1629.
[12] R. Colby, T. Meyers, The Encyclopedia of Technical Market Indicators, Dow-Jones Irwin, 1988.
[13] B.V. Dasarathy, Information fusion: what, where, why, when, and how? Inf. Fusion 2 (2) (2001) 75–76.
[14] J.C. Dempster, A realtime adaptive trading system using genetic programming, Quant. Finance 1 (2001) 397–413.
[15] T. Di Matteo, Multiscaling in finance, Quant. Finance 7 (1) (2007) 21–36.
[16] Dsto (defence science and technology organization) data fusion special interest group, Data fusion lexicon, 1994.
[17] N. Hachicha, B. Jarboui, P. Siarry, A fuzzy logic control using a differential evolution algorithm aimed at modelling the financial market dynamics, Inf. Sci. 181 (2011) 79–91.
[18] A.C. Harvey, Forecasting, Structural Time Series Models and the Kalman Filter, Cambridge University Press, 1989.
[19] J. Hung, A fuzzy asymmetric garch model applied to stock markets, Inf. Sci. 179 (2009) 3930–3943..
[20] G. Iovane, L. Puccio, G. Lamponi, A. Amorosia, Electronic access key based on innovative information fusion tecniques involving prime numbers and biometric data, J. Discrete Math. Sci. Cryptogr. 4 (13) (2011) 207–225.
[21] D. Kahneman, A. Tversky, Prospect theory: an analysis of decision under risk, Econometrica 77 (2) (1979) 263–291.
[22] A. Karlsson, Dependable and Generic High Level Information Fusion Methods and Algorithms for Uncertainty Management, Technical Report, HSIKI TR07003., 2007.
[23] G. Lane, Lane's stochastic, in: Second issue of Technical Analysis of Stocks and Commodities Magazine, 1984, pp. 87–90.
[24] Q. Li, J. Wang, Y. Chen, Z. Lin, User comments for news recommendation in forum based social media, Inf. Sci. 180 (2010) 4929–4939.
[25] Q. Li, T. Wang, P. Li, L. Liu, Q. Gong, Y. Chen, The effect of news and public mood on stock movements, Inf. Sci. 278 (2014) 826–840.
[26] J. Llinas, C. Bowman, G. Rogova, A. Steinberg, E. Waltz, F. White, Revisiting the JDL data fusion model II, in: Seventh International Conference on Information Fusion, 2004, pp. 1218–1230.
[27] R. Luo, C. Yih, K. Su, Multisensor fusion and integration: approaches, applications, and future research directions, IEEE Sens. J. 2 (2) (2002) 107–119.
[28] R. Mantegna, H. Stanley, An Introduction to Econophysics: Correlation and Complexity in Finance, Cambridge University Press, 2000.
[29] A. Marszalek, T. Burczynski, Modeling and forecasting financial time series with ordered fuzzy candlesticks, Inf. Sci. 273 (2014) 144–155.
[30] J.L. McCauley, Thermodynamics analogies in economics and finance: instability of markets, Physica A 329 (1–2) (2003) 199–212.
[31] M. Mehlawat, Credibilistic mean-entropy models for multi-period portfolio selection with multi-choice aspiration levels, Inf. Sci. 345 (2016) 9–26.
[32] R. Morales, T. Di Matteo, T. Aste, Non stationary multifractality in stock returns, Physica A 392 (24) (2013) 6470–6483.
[33] P. Olsson, B. Nilsson, B. Gawronska, A. Persson, T. Ziemke, S. Andler, An information fusion approach to controlling complexity in bioinformatics research, in: IEEE Computational Systems Bioinformatics Conference Workshops, 2005, pp. 299–304.
[34] T. Plummer, Forecasting Financial Markets: A technical Analysis and the Dynamic of Price, Wiley Finance Edition, 1991.
[35] A. Ross, A. Jain, Information fusion in biometrics, Pattern Recognit. Lett. 24 (13) (2003) 2115–2125.
[36] G.W. Schwert, Why does stock market volatility change over time? J. Finance 44 (5) (1989) 1115–1153.
[37] P. Smart, Knowledge intensive fusion for improved situational awareness, in: 2nd Annual DIF DTC Conference, 2005.
[38] A. Steinberg, C. Bowman, Rethinking the JDL data fusion levels, in: NSSDF Conference Proceedings, 2004.
[39] A. Steinberg, C. Bowman, F. White, Revisions to the JDL data fusion model, Sens. Fusion (1999).
[40] M. Thomsett, Chaikin Money Flow: Changes Anticipating Price Reversal, Financial Time Press, 2010.
[41] L. Wald, Some terms of reference in data fusion., IEEE Trans. Geosci. Remote Sens. 37 (1999) 1190–1193.
[42] E. Waltz, J. Llinas, Multisensor Data Fusion, Artech House Inc., 1990.
[43] J. Welles Wilder, New Concepts in Technical Trading Systems, Trend Research, 1978.
[44] F.E. White, Data Fusion Lexicon, 1991. U.S. Department of Defence - Data fusion subpanel of the joint directors of laboratories, technical panel for c3
[45] B. Williams, New Trading Dimensions: How to Profit from Chaos in Stocks, Bonds, and Commodities, Wiley, 1998.
[46] J. Yao, C. Tan, A case study on using neural networks to perform technical forecasting of forex, Neurocomputing 34 (2000) 79–98.
[47] X. Zhang, Non linear predictive models for intraday foreign exchange trading, Int. J. Intell. Syst. Account. 17 (13) (1994) 481–495.
[48] X. Zheng, B.M. Chen, Identification of stock market forces in the system adaptation framework, Inf. Sci. 265 (2014) 105–122.